Association for Information Systems
AIS Electronic Library (AISeL)

MCIS 2007 Proceedings

Mediterranean Conference on Information Systems (MCIS)

2007

THE IMPACT OF USE OF INTELLIGENT AGENTS TECHNOLOGY ON USER PERCEPTION: TESTING TTF MODEL

Fourati Fatma
University of Paris Dauphine, fatma.fourati@dauphine.fr

THE IMPACT OF USE OF INTELLIGENT AGENTS TECHNOLOGY ON USER PERCEPTION: TESTING TTF MODEL

Fatma, Fourati, University of Paris Dauphine, Place du Maréchal de Lattre de Tassigny – 75775 Paris Cedex, France, fatma.fourati@dauphine.fr

Abstract

We define in this paper how the causality between the use of technology of Intelligent Agents and the perception on the users arises and how information systems literature has already investigated this causal coherence.

The aim of this article is to study the impact of use of intelligent agent technology on individual perception. To respond to this question we have tried to research for the relationship between the needs of this technology and the intensity of its usage. To examine this relationship, we have based our study to use the model of Task-Technology Fit (Goodhue & Thompson, 1995). To have data about intelligent agent users, we have mailed a survey to 750 companies of different sectors in France. This survey was oriented to diverse users (directors, designers, analysts…). We have received 155 responses that were found to be completed, and sound for use. A quantitative method can be used to process these data and conclude positive results. Among this study, we have tried to show the use of Intelligent Agents and their business applications.

We indicate that the positive effect of task, technology characteristics on task-technology fit (TTF) constructs can be empirically attested, that these results are valid and reliable and how these findings affect the specific application domain.

Keywords: Task-Technology Fit (TTF) Model, Intelligent Agents.

1. INTRODUCTION

The purpose of this paper is to identify the underlying items of the Task-Technology Fit for purpose and use it in conjunction with Intelligent Agents.
First, we proposed some definitions of Intelligent Agents in order to understand the reasons of this technology.
Second, we demonstrated the existence of relationship between task and technology characteristics on the TTF constructs.
Third, we tried to search the impact of this task, technology characteristics and TTF constructs on utilization behavior. We based our study in this model because his application focuses on actual use or degree of software utilization.
The objective of this research is to evaluate TTF model in understanding IA utilization. We examined this model using path analytic techniques, specifically the PLS-Graph (Chin, 1998).
In this article, we have discussed Intelligent Agents utilization by exploiting a survey of 155 business managers. The findings and implications of the study are discussed in paragraph 4. We have concluded some potential research questions, which will help to develop more reliable tools for measure.

2. LITERATURE REVIEW: INTELLIGENT AGENTS

There is wide literature that proposes some definitions to this new technology. The definition that seems to be of our interest was proposed by Wooldridge and Jennings (1995): "The term agent is used to denote a hardware or software-based computer system that features the following characteristics:

- *Autonomy*: agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state;
- *Social ability*: agents interact with other agents (and possibly humans) via some kind of agent-communication language[1];
- *Reactivity*: agents perceive their environment, (which may be the physical world, a user via a graphical user interface, a collection of other agents, the Internet, or perhaps all of these combined), and respond in a timely fashion to change what occur in it;
- *Pro-activeness*: agents do not simply act in response to their environment, they are able to exhibit goal-directed behavior by taking the initiative."

Other characteristics attributed to intelligent agents (Rudowsky, 2004):

- *Mobility*: the ability is to move around an electronic environment;
- *Learning / adaptation*: agents improve performance over time.

The abovementioned characteristics can determine the degree of intelligence.
Intelligent Agents can be studied by different disciplines such as: Artificial Intelligence that is interested in studying the components of intelligence, advanced databases and knowledge base systems, cognitive psychology, distributed information systems, information retrieval, and human interaction with computer.
In our case, this technology is processed in the domain of Information Systems Management in order to explicit the functionality facet of this technology.
The use of Intelligent Agents can be a means and there are also many other solutions, a solution that provides real meaning. In addition, this solution is needed to assist in searching, filtering, and deciding what is relevant to the user (Rudowsky, 2004).
This paper describes the agent's tasks in the business context and what benefits their usage carries with it :

- Gathering diverse information sources: the user should collaborate with software agent. However, it is difficult to exploit it to its full due to the large amount of unstructured, redundant and irrelevant information available. So the web mining has abundant techniques for

[1] M.R. Genesereth & S.P. Ketchpel. Software agents. Communications of the ACM, 37 (7) : 48-53, July 1994.

analyzing, disseminating and communicating information. (Using General Search Agents, Meta-Search Engines, Personalized Web Crawlers…)

- Processing information: the manager or user of new technologies to process uncertain, dynamic and incomplete information would benefit from the capability of these technologies. Intelligent agent is a support tool that extracts, processes, classifies and updates the data contained in the web with little supervision from the user. As a result, we expect companies that use the IA technology to benefit by improving their competitiveness. (Using Focused Spiders, Intelligent Agents, Text Mining…)
- Diffusion and disseminating information: the use of this technology facilitates the communication between the users and keeps everyone in the organization informed. Then these findings were presented to decision makers. (Using Intranet, Lotus Notes, Knowledge Bases…)

The enhancement of communication between users does not compulsorily lead to situations where information proliferation (i.e. the increasing flood of information for decision makers) can be reduced by the usage of agents. It is possible, by all means, that agents are appropriate for collecting information, but not efficient in filtering the crucial ones.

We have tried to research for the relationship between the needs of this technology and the intensity of use. To examine this relationship, one significant model of information technology behavior was emerged in the Management Information Systems literature. The Task-Technology Fit model (TTF) provide a theoretical basis for discovering the factors that explain the user task needs, the functionalities of the information technology and their impact on the intensity of use. We present in the next section this model by defining the specific constructs for measurement in the survey.

3. RESEARCH METHOD

An online survey was used to collect data. The goals of this study, authority and tasks were clearly stated on the cover page to induce the confidence of respondents to perform this survey. Results of the survey were given to increase response rate.

We have based on the definition of Intelligent Agents; examples of IA systems were also included in order to increase accuracy of responses and on the research findings of the Information systems literature to build a survey with 36 items and to validate the coherence between the items and their constructs.

Respondents were asked to specify an IA system that they have been using within their organization. Yet, we have not requested a question about their experience with a particular system. In fact, experiences, being seen as an important aspect in the research field of IT usage (Venkatesh and Davis, 2000), were not considered in the conducted analysis. This aspect needs to be discussed in further research.

We have tested the questionnaire items in collaboration with two professional's experts of IA technology, to gather opinions, find out errors and perform the design of online survey. The questionnaire was refined, based on the results from the pre-test and other comments of the survey participants. They were asked to answer the questions on a seven-point Likert scale, where 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Neutral, 5 = Somewhat agree, 6 = Agree, 7 = Strongly agree. This scale is designed for all items.

The constructs used for measurement in the questionnaire are subsequently discussed:

Task-Technology Fit (TTF)

This construct has been measured by Goodhue (1993). From Goodhue's instrument we borrowed multiple questions of six dimensions of TTF addressing the extent to which existing information systems support the identification, access, and interpretation of data for decision making.

Based on the composite reliability assessment and discriminant validity of the questions, seven questions (and 1 dimension) were dropped as being unsuccessfully measured. We have applied and modified the Goodhue's approved model in order to appropriate it for this situation.

The final five components of TTF that were successfully measured included: **Data Quality (QD), Locatability of Data (LD), Data Compatibility (CD), Systems Reliability (SR) and Quality of service of IA (QS)**. The first three dimensions focused on meeting task needs for using data in decision making. The next one focused on meeting day-to-day operational needs, and the last focused on responding to change business needs.

Task Characteristics (TaC)

Task characteristics and their impact on information use have been studied by a great many researchers (Culnan, 1983; Daft and Macintosh, 1981; O'Reilly 1982). We have used Goodhue combined Perrow's (1967) and Thompson's (1967) dimensions. In our survey, we have supposed two dimensions of task characteristics: Task equivocality (lack of analyzable search behavior) and interdependence (with other organizational units). Two measures of task characteristics (on interdependence, the other two questions on non-routineness were ejected) were adopted from Goodhue's study.

Technology Characteristics (F)

Goodhue and Thompson's (1995) measure are focused on two proxies for the underlying characteristics of the technology of IS: first, the information systems used by each respondent and second the department of the respondent.

We can measure the effect of this technology (Systems Used) and the department of respondents on TTF by using variance analysis within SPSS. (Fourati, 2006)

Our study focused on functionalities of Intelligent Agents, because studying such a wide range of issues for an emerging technology represents a complex and multidisciplinary task. We have tried to develop a reliable tool to measure and discover four Intelligent Agent functionalities. (Fourati, 2005)

Intensity of use (IU)

This construct should be measured as the proportion of times users choose to utilize intelligent agents. This proportion was extremely difficult to ascertain in a field study. There was also the problem of mandatory use (Goodhue & Thompson, 1995).

To conceptualize utilization as the extent to which the information systems have been integrated into each individual's work routine. It reflects the individual choice to accept the intelligent systems. We operationalized this by asking users to precise the amount of time (in total hours and/or minutes) using the IA per day.

Based on an assessment of the composite reliability of the questions, three items were dropped as being successfully measured.

Figure 1 shows TTF model and all relations between these variables:

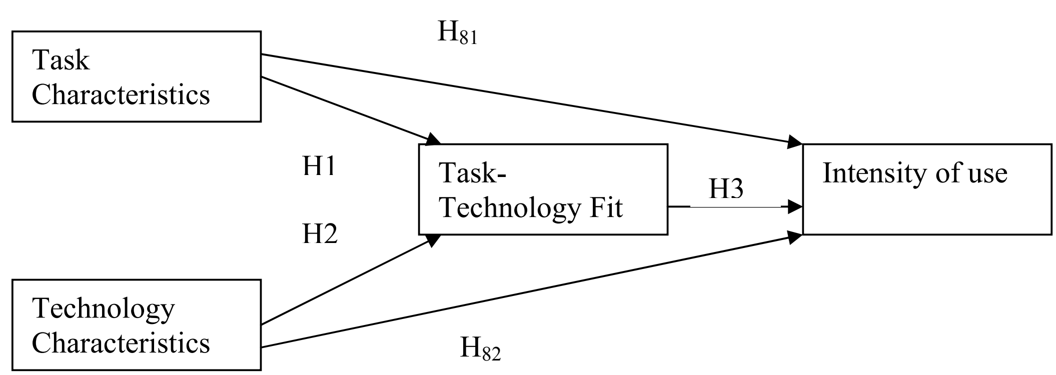

Figure 1. TTF Model

4. ANALYSIS AND RESULTS

Three general sets of methodological consideration are relevant to the application of PLS in a management research context: (I) assess the reliability and validity of measures; (II) determine the appropriate nature of the relationships between measures and constructs; and (III) interpret path coefficients, determine model adequacy, and select a final model from the available set of alternatives. (Hulland, 1999)

4.1. Assessing the reliability, validity of measures and relationships between measures and constructs

Although PLS estimates parameters for both the links between measures and constructs (loadings) and the links between different constructs (path coefficients) at the same time, a PLS model is usually analyzed and interpreted in two stages:

- The assessment of the reliability and validity of measurement model followed by,
- The assessment of the structural model.

This sequence ensures that the researcher has reliable and valid measures of constructs before attempting to draw conclusions about the nature of the construct relationships. (Hulland, 1999)

The adequacy of the measurement model can be assessed by looking at:

- Individual item reliabilities,
- The convergent validity of the measures with individual constructs, and
- The discriminant validity. (Hulland, 1999)

Table 1 illustrates the loadings, composite reliabilities, and Average Variance Extracted (AVE) that were used in the tests.

Constructs	Measurement Items	Loading	Composite Reliability	Average Variance Extraction (AVE)
Task Characteristics (TaC)	Item28 Item29	0.90 0.97	0.935	0.878
Technology Characteristics (IA Functionalities) (F)	Item51 Item52 Item54	0.85 0.84 0.79	0.870	0.690
Data Quality (QD)	Item3 Item5 Item6	0.87 0.87 0.89	0.913	0.778
Locatability of Data (LD)	Item7 Item8 Item9 Item10	0.88 0.86 0.87 0.86	0.927	0.760
Data Compatibility (CD)	Item13 Item14 Item15	0.87 0.87 0.74	0.867	0.686
Systems Reliability (SR)	Item16 Item17	0.78 0.76	0.753	0.604
Quality of service of IA (QS)	Item20 Item22 Item23 Item25	0.84 0.85 0.87 0.84	0.914	0.726
Intensity of use (IU)	Item57 Item58 Item59	0.86 0.90 0.74	0.877	0.705

Table 1. Results of Confirmatory Factor Analysis

First, in PLS individual item reliability is assessed by examining the **loadings** of the measures with their respective construct**.** According to Chin (1998), “standardized loadings should be greater than 0.707”, which implies that there is more shared variance between the construct and its measure than error variance (Carmines and Zeller, 1979). Since loadings are correlations, this implies that more than 50 percent of the variance in the observed variable (i.e., the square of the loading) is due to the construct.
In practice, if an estimated model has loadings less than 0.707, we eliminate the item particularly when new items or newly developed scales are employed. For all constructs, most of items had reasonably high loadings (above 0.707) with the majority over 0.8, therefore demonstrating convergent validity. Very few items had loadings below 0.7 and these were eliminated.
Second, when multiple measures are used for an individual construct, the researcher should be concerned not only with individual measurement item reliability, but also with the extent to which the measures demonstrate **convergent validity** (Hulland, 1999). Traditionally, researchers using PLS have reported one or both of two measures of convergent validity: Cronbach’s alpha and the internal consistency[2] measure developed by Fornell and Larcker (1981). These authors argue that their measure is superior to alpha since it uses the item loadings obtained within the nomological network. The interpretation of the values obtained is similar, and the guidelines offered by Nunnally (1978) can be adopted for both. Nunnally suggests 0.7 as a benchmark for “modest” composite reliability, applicable in the early stages of research[3]. These values are reported in column four of Table 1 in this study.

	AVE	TaC	F	QD	LD	CD	SR	QS	IU
TaC	0.878	0.937							
F	0.690	0.542	0.830						
QD	0.778	0.411	0.626	0.882					
LD	0.760	0.492	0.684	0.805	0.871				
CD	0.686	0.353	0.477	0.234	0.274	0.828			
SR	0.604	0.508	0.646	0.636	0.681	0.469	0.777		
QS	0.726	0.594	0.719	0.644	0.718	0.422	0.646	0.852	
IU	0.705	0.372	0.333	0.367	0.392	0.306	0.416	0.314	0.839

Legend:
Task Characteristics (TaC)
Technology Characteristics (IA Functionalities)(F)
Data Quality (QD)
Locatability of Data (LD)
Data Compatibility (CD)
Systems Reliability (SR)
Quality of service of IA (QS)
Intensity of use (IU)

Table 2. Average Variance Extracted values & Correlation among constructs in PLS Analysis

[2] Internal consistancy = $((\sum \lambda_{yi})^2 / ((\sum \lambda_{yi})^2 + \sum \mathrm{var}(\epsilon_j))$.
[3] This discussion of convergent validity and the preceding discussion of item reliability can only be applied to measures that are reflective, rather than formative. (Hulland J. 1999).

In assessing the internal consistency, we looked at the composite reliability measure (ρ) developed by Werts et al. The composite reliability measures provided additional support for reliability and convergent validity. (Khalifa & Cheng, 2002).

After generating Bootstrap, all composite reliability for each construct is over 0.80 except the construct of systems reliability but his AVE is over than 0.50 (shown in Tab.1)

The convergent validity of the construct used for this model appear**s** to be acceptable.

Third, additional methodological complement to convergent validity is **discriminant validity**, which represents the extent to which measure of a given construct differ**s** from other constructs measures in the same model. In a PLS context, one criterion for adequate discriminant validity is a construct that should share more variance with its measures than it shares with other constructs in a given model (should share more variance with its indicators of measure). (Hulland, 1999). To assess discriminant validity, Fornell and Larcker (1981) suggested the use of Average Variance Extracted [4] (The average variance shared between a construct and its measures).

This measure should be greater than the variance shared between the construct and other constructs in the model (the squared correlation between two constructs). This can be demonstrated in a correlation matrix which includes the correlations between different constructs in the lower left off-diagonal elements of the matrix, and the square roots of the AVE values calculated for each of the constructs along the diagonal. For adequate discriminant validity, the diagonal elements should be significantly greater than the off-diagonal elements in the corresponding rows and columns (Hulland, 1999). We report AVE, Root AVE and inter-construct correlations in Table 2, providing clear evidence of discriminant validity.

4.2. Interpreting path coefficients

To simplify the interpretation of results, we can treat each hypothesis of the model apart.

H1: Task characteristics have a positive impact on Task-Technology Fit.

H2: Technology characteristics have a positive impact on Task-Technology Fit.

These two hypotheses generate some **10 hypotheses** (see Table 3).

Do Task and Technology Characteristics predict TTF?

	TaC (V1)	T-Statistic[5]	F (V2)	T-Statistic
QD (V3)	0.102 (H_{31})	1.0645 (n.s.)	0.570 (H_{32})	5.7805 (**)
LD (V4)	0.171 (H_{41})	2.0542 (*)	0.591 (H_{42})	7.5092 (**)
CD (V5)	0.135 (H_{51})	1.5260 (n.s.)	0.404 (H_{52})	4.6171 (**)
SR (V6)	0.224 (H_{61})	3.0779 (**)	0.524 (H_{62})	9.0371 (**)
QS (V7)	0.289 (H_{71})	3.9717 (**)	0.563 (H_{72})	8.0497 (**)

*Table 3. The influence of Task and Technology Characteristics on TTF Constructs: Path analysis (** = 0.005, * = 0.025)*

Task and technology characteristics explained 40% of the variance in quality of data (QD). Technology characteristics had the strongest effect with a path coefficient of 0.57. Task characteristics had a weaker effect with a path coefficient of 0.102.

We noted a good explanatory power for Quality of system (QS) with over 57% of the variance explained. The effect of technology characteristics is however more dominated with a direct

[4] $AVE = \sum \lambda_{yi}^2 / (\sum \lambda_{yi}^2 + \sum var(\epsilon_j))$.

[5] Our sample is from 155 participants: If T>=1.96, so we have a level of signification: $p < 0.025$ and If T>=2.57, so we have a level of signification: $p < 0.005$

path coefficient of 0.563 in comparison to task characteristics (path coefficient = 0.289). (We note the same remarks with Locatability of data, Compatibility of data and Reliability of systems)

In addition, we noted a bad explanatory power for the Compatibility of data with $R^2 = 24\%$. So, the effect of technology characteristics is more important with a path coefficient of 0.404 in comparison to task characteristics (path coefficient = 0.135).

Effect of Task Characteristics on TTF:

Goodhue & Thompson (1995) measured task by taking consideration of non-routineness, interdependence of task and the job title of participant. They found the strongest effect of task characteristics was from non-routine tasks. They explained this with the idea that these people are constantly forced to use information systems to address new problems, such as seeking out new data and combining it in unfamiliar ways. Thus, they make more requirement on systems. Interdependence of job tasks was observed to influence perceptions of the compatibility and reliability of systems. Finally, two factors of TTF are clearly affected by job level: compatibility and ease of getting authorization for access.

In our study, the items measuring task equivocality were eliminated, so task characteristics was measured by only interdependence and we confirm some of the findings of Goodhue and Thompson, three factors of TTF that are affected by this: reliability of systems (SR), quality of service (QS) and locatability of data (LD). (See t-statistic in table 3)

In this article, we have not presented the job level influence on TTF variables. We can examine this relation by using the variance analysis with SPSS. This is the case of other variables like: Systems used and department.

Effect of Technology Characteristics on TTF:

Goodhue & Thompson have considered two proxies for characteristics of the technology: “systems used” and “department”. They were significant predictors together for four of the eight factors of TTF. Department is a significant predictor of user evaluations of production timeliness and of training/ease of use. Systems used are a significant predictor of locatability and systems reliability. We limited our study by testing the influence of IA functionalities on TTF variables. We will verify in other paper the influence of these two variables on TTF by using variance analysis, in order to compare our findings with Goodhue & Thompson.

The IA Functionalities would influence the five TTF components taken into consideration in our model. All relations are positives and have significant impact. (See t-statistic table 3)

To justify this influence, we can think that the functionalities of this technology help the user to maintain the necessary elements for data or to maintain the data at the right level. Also, the functionalities of IA help the user to determine what data is available, where and/or what is excluded. These functionalities influence the Systems Reliability, on the other terms the dependability and consistency of access of systems. Here, the user perceived the uptime of IA systems on one hand, and perceived that these systems used can be subject to unexpected problems which make it harder to use in his work, on the other hand.

Finally, these functionalities had a great effect on locatability of data (path coefficient = 0.591); this can be explained by the evidence of real interest of IA in helping the user to search information at the right sources.

H3: Task-Technology Fit has a positive impact on Intensity of use of Intelligent Agents.

The study of H3 generates **five hypotheses** (see Table 4)

$\mathbf{H_{81}}$: Task Characteristics has a positive impact on the Intensity of use of IA.

$\mathbf{H_{82}}$: Technology Characteristics has a positive impact on the Intensity of use of IA.

Does TTF predict Intensity of use of IA?

	TaC (V1)	F (V2)	QD (V3)	LD (V4)	CD (V5)	SR (V6)	QS (V7)
IU (V8)	0.214 (H_{81})	-0.059 (H_{82})	0.132 (H_{83})	0.179 (H_{84})	0.170 (H_{85})	0.165 (H_{86})	-0.163 (H_{87})
T-Statistic	2.0752 (*)	0.4505 (n.s.)	0.8851 (n.s.)	1.0392 (n.s.)	1.3856 (n.s.)	1.1900 (n.s.)	0.8304 (n.s.)

Table 4. The influence of Task and technology characteristics, TTF on the Intensity of Utilization of IA: Path analysis (= 0.025)*

Quality of data, Locatability of data, Compatibility of data, Reliability of systems, Quality of services, Task and technology characteristics explained 24% of the variance in Intensity of use of Intelligent agents. Locatability of data has a great effect, with a path coefficient of 0.179. This effect is non significant. The task characteristics (path coefficient = 0.214) have a greatest effect on the Intensity of Use. This relation is positive and significant. (see Table 4)

If we refer to Goodhue and Thompson, by showing the arrow from TTF to Utilization, we would find that their results provide little support for the hypothesized relation. Although the regression as a whole and three of the path coefficients were statistically significant (Relationship, Timeliness and Reliability), the adjusted R^2 was only 0.02. In addition, reliability of systems and relationship with IS had negative path coefficients.

Our results show that compatibility of data (CD), locatability of data (LD) and reliability of systems (SR) have the strongest effect on intensity of use. It leads us to explain that some participants of this surveys and who are very depending on IA systems (higher intensity of use) consider these systems as reliable. Also, the data from different sources propose to the users using IA in order to search or compare the compatibility of data and to determine what and where data is available. So we observed that the need of this technology increases the frequency of use.

Goodhue and Thompson gave more explanation that the direct link between TTF and utilization may not be justified in general. For them, TTF may not dominate the decision to utilize technology. Rather, other influences from attitudes and behavior theory such as habit (Ronis et al., 1989), social norms (and mandated use) may dominate at least in these organizations. This would suggest that testing the link between TTF and utilization requires much more detailed attention to other variables from attitudes and behavior research.

5. CONCLUSION

Our results indicate a positive relationship between task, technology characteristics and TTF constructs. Fit increases as task interdependence and functionalities of IA increase. This result is also supported by previous research (Goodhue & Thompson, 1995). We show in this study, the direct effect of task characteristics on intensity of use contrasts with the negative and non-significant effect of tool functionalities. We note the same remark with effect of tool quality services.

Our TTF model can help researchers and practitioners better to understand why managers choose to IA technology for particular tasks.

References

Carmines, E. G. and Zeller R.A. (1979). Reliability and validity assessment. Sage University Paper Series on Quantitative Applications in the social sciences, n° 07-017, Sage, Beverly Hills, CA.
Chin W. (1998). Issues and opinion on structural equation modeling. MIS Quarterly, 22 (1), 7-16.
Cunlan M.J. (1983). Environmental scanning: the effects of task complexity and source accessibility on information gathering behavior. Decision Sciences, 14, 194-205.
Fornell, C and Larcker D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18, February, 39-50.
Fourati F. (2005). Measuring user satisfaction with Intelligent Agents: An exploratory study. Presented at sixth international conference on data mining, text mining and their business applications, Skiathos, Greece, May 25-27, 2005, published in Data Mining VI, ISSN 1743-3517, p. 389-398, WIT Transactions on Information and Communication Technologies, Vol. 35, WIT Press. www.witpress.com
Fourati F. (2006). Veille stratégique: L'évaluation de l'utilisation des agents intelligents. Thèse, Université Paris Dauphine.
Goodhue, D. L. (1995). Understanding User Evaluations of Information Systems. Management Science, 41 (12), 1827-1844.
Goodhue, D. L. and Thompson R. L.(1995). Task-Technology Fit and Individual Performance. MISQ, 19 (2), 213-236.
Hans Chalupsky, Yolanda Gil, Craig A. Knoblock, et al. (2001). Electric Elves: Applying agent technology to support human organizations. Copyright 2001, American Association for Artificial Intelligence (www.aaai.org). All rights reserved.
Khalifa M. and Cheng S.K.N. (2002). Adoption of mobile commerce: Role of exposure. Proceedings of the 35th Hawaii International Conference on System Sciences.
Nunnally, J.C. (1978). Psychometric theory. 2nd Edition. New York ; McGraw-Hill.
Perrow, C. (1967). A framework for the comparative analysis of organizations. American Socialogical Review, 32 (2), 194-208.
Ronis, D.L., Yates J.F., Kirscht J.P. (1989). Attitudes, decisions and habits as determinants of repeated behavior. In A.R. Pratkanis, S.J. Breakler, A.G. Greenwald (Eds.). Attitude structure and function, p.213-239.
Rudowsky I. S. (2004). Intelligent Agents. Communications of the Association for Information Systems, 14.
Sycara, K. Decker, K., Zeng, D. (1999). Intelligent agents in portfolio management. In Agents Technology Foundations, Applications and Markets, eds, N. Jennings and M. Woolridge. Springer.
Venkatesh, V. and Davis, F. (2000). A theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Management Science, 46 (2), 186-204.
Werts C.E., Linn R.L. and Joreskog K.G. (1974). Intraclass Reliability Estimates: Testing Structural Assumptions. Educational and Psychological Measurement, 34, 25-33.
Wooldridge M. and Jennings N.R. (1995). Intelligent Agents: Theory and Practice. The Knowledge Engineering Review, 10 (2).